Cricket Ball Prediction Model V2: Unified Heterogeneous Graph Architecture

Architecture Documentation

December 16, 2025

Abstract

This document describes Version 2 of the cricket ball prediction model. The key innovation is representing **all information as a single heterogeneous graph**, eliminating the separation between spatial and temporal processing. This enables full innings history while maintaining computational efficiency.

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1 Overview

1.1 The Core Idea

Instead of separate spatial and temporal streams, **everything becomes one heterogeneous graph**.

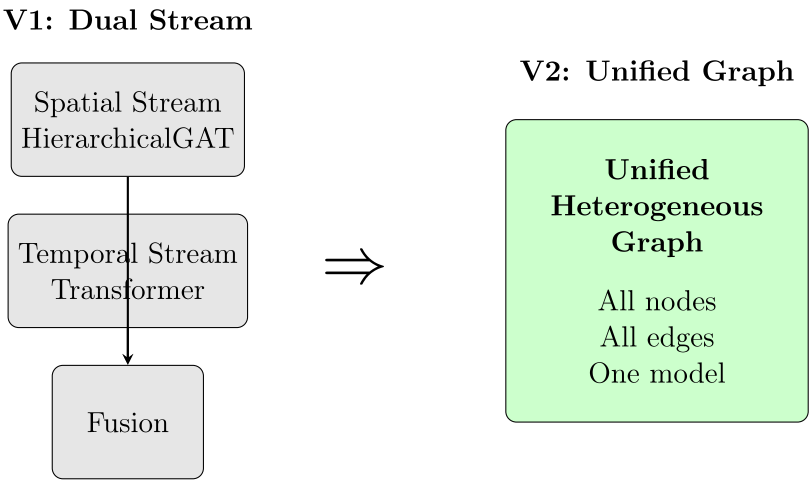


Figure 1: Architecture evolution from V1 (dual stream) to V2 (unified graph)

1.2 Why This Matters

Aspect	V1 (Dual Stream)	V2 (Unified Graph)
History length	Fixed 24 balls	Full innings
Complexity	$O(n^2)$ attention	O(edges)
Same-bowler patterns	Soft attention bias	Explicit edges
Information flow	Separate then fuse	Unified message passing
Framework	Mixed PyTorch/PyG	Full PyTorch Geometric

2 The Unified Graph Structure

2.1 Node Types

The graph contains **6 node type categories** with **21 context nodes**:

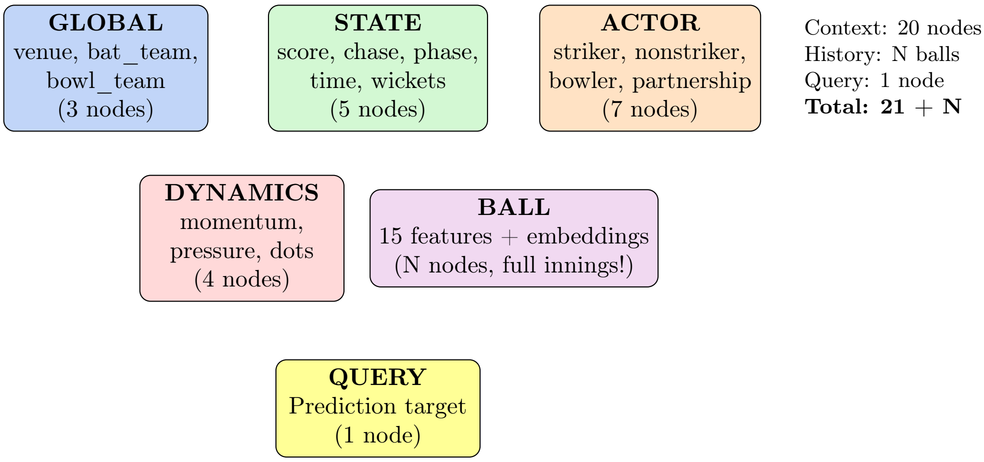


Figure 2: Six node type categories in the unified graph

2.2 Edge Types

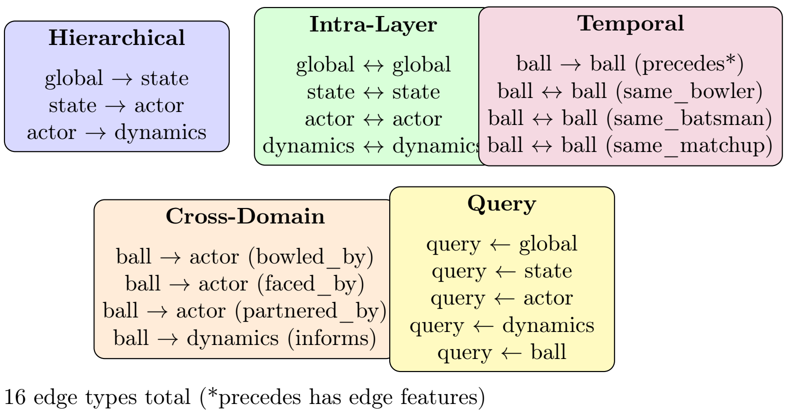


Figure 3: Edge type categories encoding different relationships

3 Full Graph Visualization

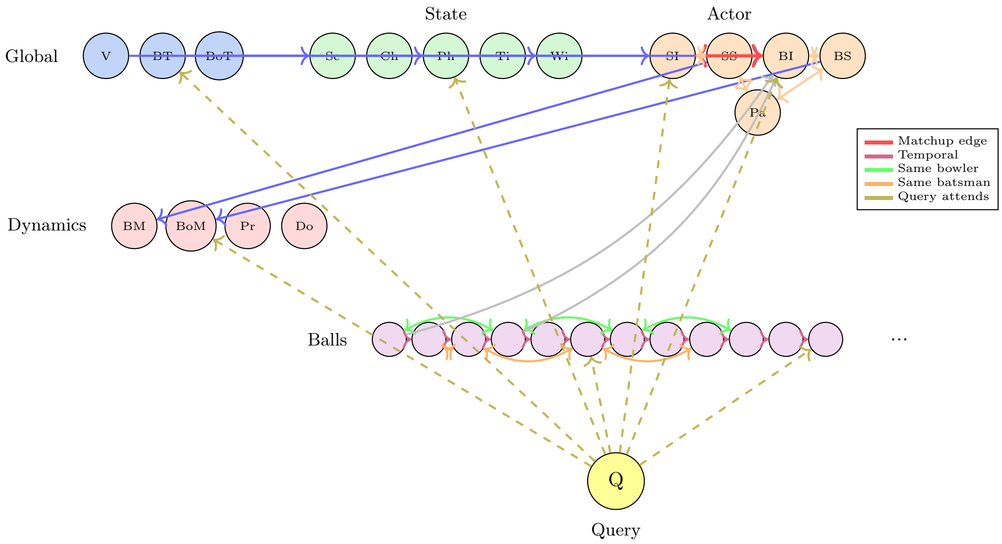
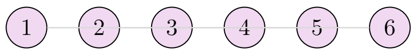


Figure 4: Complete unified graph structure showing all node and edge types

4 Why Full History Now Works

4.1 The Quadratic Problem (V1)

In V1's Transformer, every ball attends to every other ball:

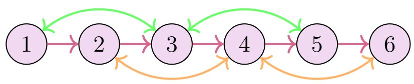


6 balls → 15 attention pairs
24 balls → 276 pairs
120 balls → 7,140 pairs

Figure 5: V1: Full attention scales $O(n^2)$

4.2 The Linear Solution (V2)

In V2's graph, attention only flows along edges:



6 balls → 11 edges
24 balls → ~100 edges
120 balls → ~500 edges

Figure 6: V2: Sparse edges scale $O(n)$

4.3 Efficiency Comparison

History Length	V1 Attention Pairs	V2 Edges	Speedup
24 balls	576	~150	4x
60 balls	3,600	~350	10x
120 balls (full innings)	14,400	~700	**20x**

Table 1: Computational comparison: V1 vs V2

5 Model Architecture

5.1 Three-Stage Pipeline

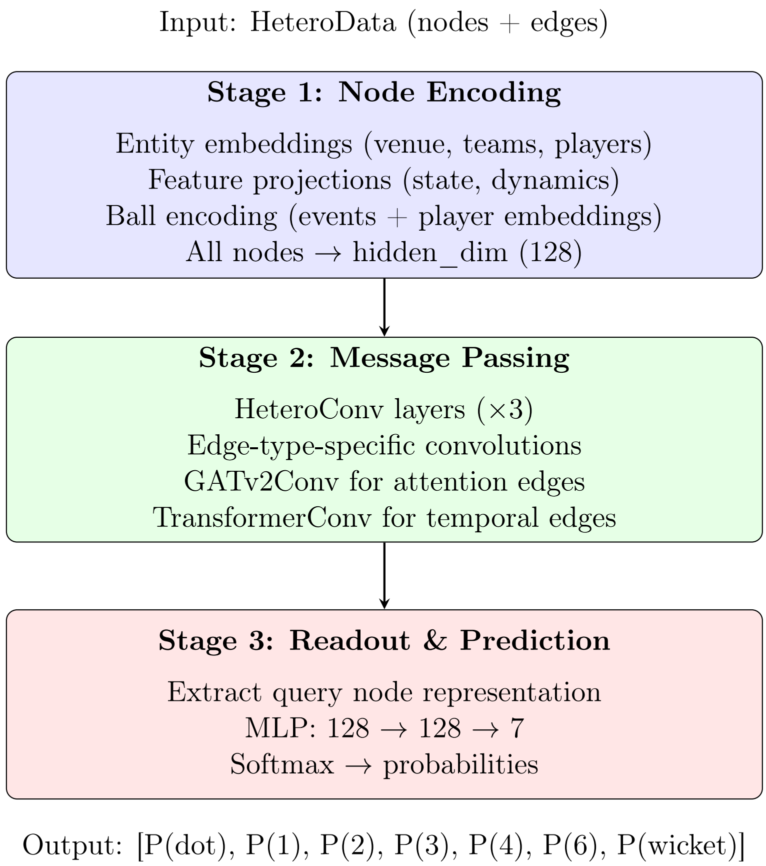


Figure 7: Three-stage model pipeline

5.2 Convolution Choices per Edge Type

Edge Type	Convolution	Rationale
Hierarchical	GATv2Conv	Attention learns which context matters
Intra-layer	GATv2Conv	Self-attention for permutation equivariance
Actor matchup	GATv2Conv	Learn matchup dynamics
Temporal (precedes)	TransformerConv	Edge features for temporal distance
Same-bowler/batsman/matchup	GATv2Conv	Aggregate spell/matchup patterns
Cross-domain (faced/bowled/partnered)	GATv2Conv	Attention-weighted recency importance
Dynamics (informs)	SAGEConv	Simple aggregation for momentum
Query	GATv2Conv	Learn what to attend for prediction

Table 2: Edge-type-specific convolution operators

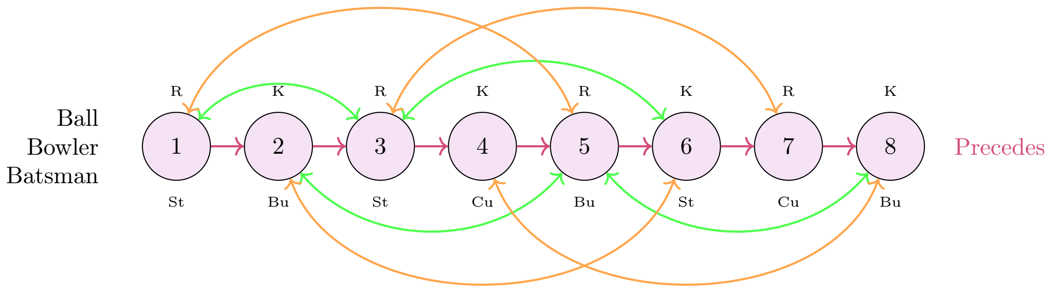
Key design decisions:

- **Cross-domain edges use GATv2Conv** (not SAGEConv): This allows the model to attend more to recent/relevant balls when aggregating a player's performance
- **Temporal edges have edge features**: The `precedes` edges carry a temporal distance attribute (closer to 0 = more recent) enabling recency-weighted attention

- **Cross-domain edges respect Z2 symmetry**: Only balls actually faced by current striker connect to striker_identity (not all balls)

6 Temporal Edge Structure

6.1 Three Types of Ball-to-Ball Edges



Precedes: Causal temporal order (ball $i \to i+1$)

Same Bowler: Balls by same bowler form cliques

Same Batsman: Balls faced by same batsman form cliques

Figure 8: Temporal edge structure enables efficient pattern learning

6.2 Why This Structure Matters

- **Precedes**: Captures immediate context, momentum shifts
- **Same Bowler**: How is this bowler's spell going? Patterns in their deliveries
- **Same Batsman**: How is this batsman building their innings?

In V1, these patterns were captured via soft attention biases.
In V2, they are **explicit graph structure** that the model must respect.

7 The Actor Matchup Graph

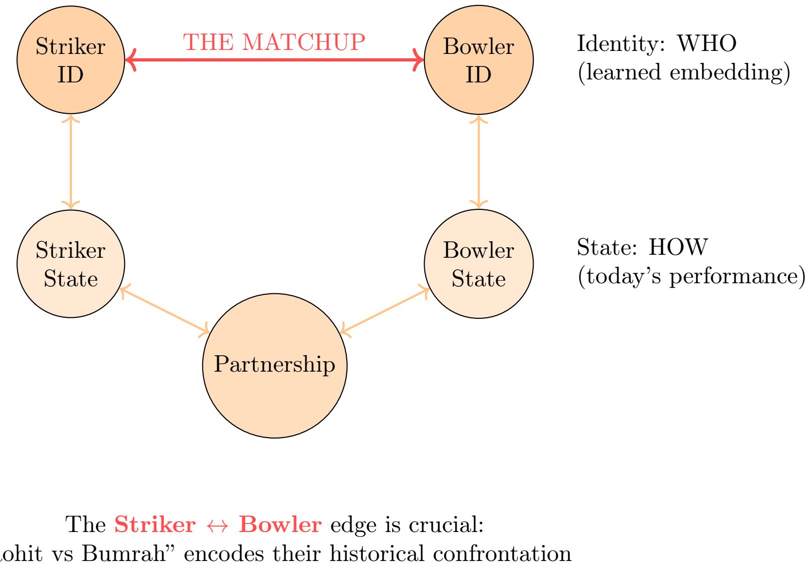


Figure 9: Actor layer graph structure (same as V1, now explicit)

8 Data Flow Summary

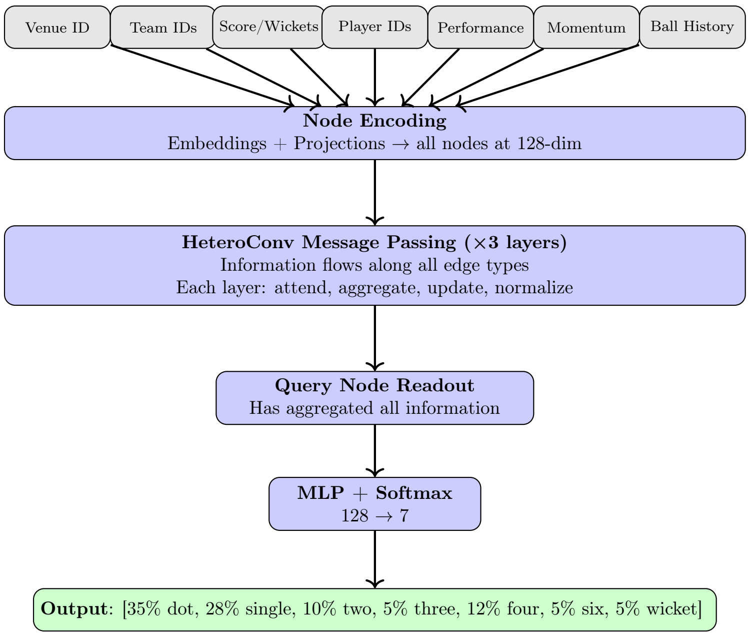


Figure 10: Complete data flow from raw inputs to prediction

9 Ball Node Features

Each ball node contains **15 numeric features** plus player embeddings:

Category	Feature	Description
Basic	runs	Normalized by 6
	is_wicket	Binary indicator
	over	Normalized by 20
	ball_in_over	Normalized by 6
	is_boundary	4 or 6 scored
Extras	is_wide	Wide ball indicator
	is_noball	No-ball indicator
	is_bye	Bye runs indicator
	is_legbye	Leg bye indicator
Wicket Type	wicket_bowled	Bowled dismissal
	wicket_caught	Caught dismissal
	wicket_lbw	LBW dismissal
	wicket_run_out	Run out dismissal
	wicket_stumped	Stumped dismissal
	wicket_other	Other dismissal types

Table 3: Ball node features (15 dimensions)

Why wicket types matter:

- **Bowled/LBW**: Indicates bowler skill, good line and length
- **Caught**: Suggests batsman aggression/risk-taking
- **Run out**: Partnership running decisions and risk assessment
- **Stumped**: Batsman error against spin bowling

Additionally, each ball has:

- **Bowler ID**: 64-dim learned embedding of who bowled
- **Batsman ID**: 64-dim learned embedding of who faced

Total ball input: $15 + 64 + 64 = 143$ dimensions $\rightarrow$ projected to hidden_dim (128).

10 Implementation Summary

10.1 Key PyTorch Geometric Components

Component	PyG Class
Data structure	`HeteroData`
Message passing	`HeteroConv`
Attention convolution	`GATv2Conv`
Temporal convolution	`TransformerConv`
Simple aggregation	`SAGEConv`
Batching	`DataLoader` (auto-batches HeteroData)

10.2 Model Configuration

Parameter	Value
Hidden dimension	128
Number of layers	3
Attention heads	4
Dropout	0.1
Number of classes	7
Estimated parameters	~720K

10.3 Training Details

- **Loss**: Cross-entropy with class weights (imbalanced outcomes)
- **Optimizer**: AdamW (lr=1e-3, weight_decay=0.01)
- **Scheduler**: Cosine annealing
- **Early stopping**: Patience of 10 epochs

11 Interpretability Benefits

The unified graph provides natural interpretability:

1. **Edge attention weights**: Which historical balls mattered most?
2. **Same-bowler attention**: How much did the bowler's spell inform the prediction?
3. **Matchup attention**: How important was the striker-bowler confrontation?
4. **Hierarchical attention**: Did global context (venue) or local dynamics drive the prediction?

All of these are directly extractable from the GATv2Conv attention weights.